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Date of Submission	05/02/2020
Date of Acceptance	20/02/2020
Date of Publication	30/03/2020
Page numbers	3606-3610 (5 Pages)

Cite This Paper: Haider Alwasiti, Mohd Zuki Y. Shredded Control of Drones via Motor Imagery Brain Computer Interface, 9(3), COMPUSOFT, An International Journal of Advanced Computer Technology. PP. 3606-3610.

ISSN:2320-0790

An International Journal of Advanced Computer Technology

SHREDDED CONTROL OF DRONES VIA MOTOR IMAGERY BRAIN COMPUTER INTERFACE

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Abstract: In this paper, we present architecture for an auxiliary shredded control that can be used in combination with a BCI control system. BCI systems are known for low reliability and accuracy. We are presenting a method to enhance this inherent weakness of BCI systems, by providing an assistive autonomous controller whenever the BCI system reaches to the point where fine control is necessary. The course control is performed by the motor imagery BCI which decodes the thinking process of the user and use it for navigating a quadcopter drone. Once the quadcopter reaches an area where the object selected to be picked up enters in the field of view of the bottom camera of the quadcopter, the autonomous controller is taking over the fine movement navigation to handle the rest of the task. This method is an exciting opportunity for several other BCI applications to enhance the reliability and accuracy of BCI systems to be adopted in everyday life of severely disabled patients.

Keywords: electroencephalogram; EEG; deep learning; drones; quadcopter; BCI; shredded control.

I. INTRODUCTION

For many people with some sort of disability, simple tasks such as picking an object is difficult[1]. Hence, the use of an assistive device, that can provide them with an independent mobility will have a big positive impact on their life[2]. The recent progress that happened in the brain computer interface (BCI) research is very promising to provide a solution for such people[3]. The aim of a BCI system is to enable the user to communicate and control device through a direct pathway from the brain to the computer, without going through the usual musculo-skeletal system. With Motor imagery BCI, it is possible to imagine the movement of different parts of the body, and the BCI system is detecting the modulated electrical brain waves to control an external device[4]. However, all types of BCIs are still not robust enough for wide adoption[5]. BCI relies on modulating the electrical brain waves (EEG) in an unnatural way, that the brain has not been adapted to[5]. However, due to the neuro-physiological basis of the human brain activity, it is difficult to isolate a single location in the brain and associate it with a single physiological task.Hence human EEG signals are always extremely noisy and mixed with signals from other natural activity of the brain and pose significant challenges to classify EEG signals associated with mental tasks[6, 7].

In this work, we are designing an additional system that compliments the BCI system to make it more robust and accurate. Typically, BCI systems are 60-90% accurate[8]. Hence, the control of the user over an external device is not accurate enough to pick an object. For example, if we have a small drone that can be controlled by a paralyzed patient, using his thinking, the current state-of-the-art of BCI systems will not guarantee that the control will be always what the user wants. Hence controlling a drone is not easy. Our proposed solution is to combine the BCI system with an additional autonomous system that helps the user to navigate the drone for picking up the object that the user wants. The desired object to be picked up is specified through selecting an object from a list displayed on a screen, using the motor imagery BCI. When selection is made, the drone will be controlled by the user's BCI, and when the drone reaches an area where its down facing camera captures the object, the object detection algorithm is switching the control from the BCI to an autonomous controller that pilots the drone and pick the object and bring it back to the user. We call such switching control as *shredded controller*, since it divides the control from the user to an autonomous controller, once it knows where is the object location and able to do the task of picking it up and bringing it to the user autonomously. Despite the effectiveness of our system to increase the accuracy of the BCI system, up to our knowledge, no previous published paper demonstrated such a design.

In the following section, we will introduce the general view over the designed system, and in later sections, each part of the proposed design is presented in detail.

II. Overall System Architecture

The proposed design is composed of: motor imagery BCI system for selecting the object images and course control of the quadcopter; quadcopter controller interface using Labview; deep learning object detection algorithm using Feature Pyramid Networks.

As schematically demonstrated in Fig.1, motor imagery BCI system is responsible for analyzing the EEG of the user to decode the intention. In our implementation, we have developed the BCI system to detect three states, namely the rest state, left hand and right hand motor imagery. The detected EEG trials is used to control selecting a list of objects shown on a screen. Left hand will move the selection and right hand will choose the object. In order to increase the accuracy of the selection process, the user is needed to repeat the selection two times, and only when the selections are matched, the BCI system would send a trigger signal to the Labview Controller.

The Labview controller is responsible for controlling the navigation operation of the quadcopter. The navigation is either performed by the user through the BCI, or auto-switched to the autonomous mode. Initially, when the selection of the object is performed on the screen, the Labview controller will switch to the manual mode of navigation, letting the user controlling the quadcopter using BCI commands. When the trigger is received from the BCI, the Labview controller will initiate the quadcopter by making it hovering on 2 meter height, and staying stationary in the x-y axis location. Two meters are an elevation where most obstacles are avoided and basically only the walls of the rooms are the limit for x-y navigation. The BCI commands are either left hand motor imagery which will rotate the quadcopter to the left, right hand

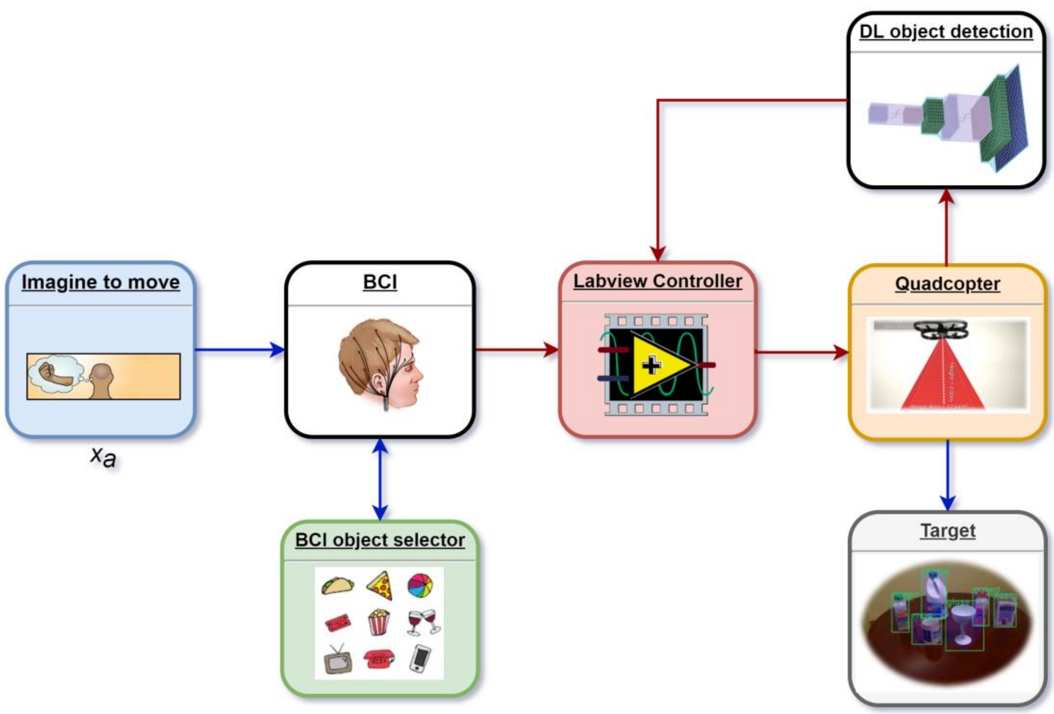

Figure 1. General system architecture of the shredded controller

motor imagery which navigates the quadcopter forward, and the rest state which makes the quadcopter hovering in a stationary x-y position. Through the use of these 3 BCI commands, it is possible to navigate the quadcopter to any position.

The quadcopter is continuously feeding the video stream of its camera to the deep learning (DL) object detection algorithm. When the the object enters in the field of view of the camera, the object is detected and the Labview controller is switched from the BCI control mode to the autonomous mode. The Labview autonomous mode, will get real time object position coordinates which is used to infer the center of the object, and to estimate how much x-axis and y-axis coordinate differences are there in relation to the center of the quadcopter. The controller will navigate the quadcopter in the x-y plane until the center of the quadcopter and the center of object matches. Then the quadcopter hovers down slowly and uses a solenoid magnetic picker to touch the object which is covered by magnetic metal sheet that is attracted to the active solenoid picker. During the hovering down the x-y plane position is constantly being corrected, to ensure proper positioning after hovering down. Once the object is picked up the Labview controller replays the navigation directions used to fly the quadcopter from the user's place to this object picked location. The error of navigation in the flying back is corrected by the front camera of the quadcopter, which is used by the same detection algorithm. When all the replay of navigation command is ordered to flyback the quadcopter, the front camera picks a special sign drawn on the wall beside the user, which is used to correct the +/- 1.5 meter error in the x-y plane position that built up during the flyback replay. Fig.2 shows the Labview control tests on the quadcopter.

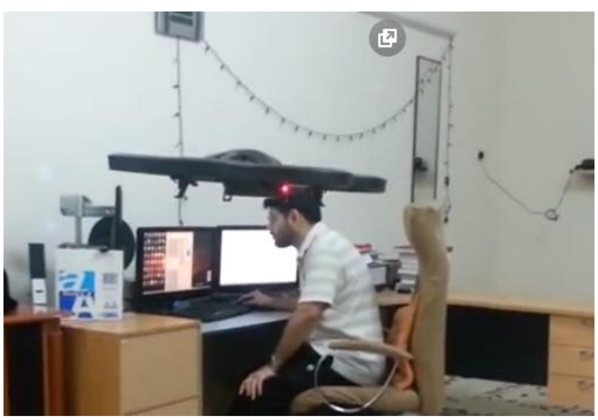

Figure 2: Labview control tests on the quadcopter

III. Motor Imagery BCI System

The EEG time series signals are converted into the frequency domain using Stockwell Transform. This transform is an enhanced version of Gabor Transform where the window size is a function of frequency, allowing better fine tuning for low and high frequency component representation.

The discrete time Stockwell transform is expressed by:
Let $\alpha = p\Delta_F$, $f = m\Delta_F$, $t = n\Delta_T$, where α is the width of the Gaussian window, Δ_F is the sampling frequency and Δ_T is the sampling interval, then:

$$S_x(n\Delta_T , m\Delta_F) = \sum_{p=0}^{N-1} X[(p+m)\Delta_F] e^{(-\pi\frac{p^2}{m^2})} e^{(\frac{j2pn}{N})} \quad (1)$$

The Stockwell Transform yielded better classification performance than Morlet. The generated spectrogram images of the frequency range of 6-78 Hz has been plotted for each channel and the whole image of spectrograms is fed into a Triplet Network, which is a deep metric learning classifier that was developed for detecting the motor imagery from Stockwell Transform spectrogram. Fig. 3 shows the principle of the Triplet Network used for the BCI.

The Triplet Network is one form of Metric Learning. The Convolutional Neural Network (CNN) encoders are trained to optimize a 256 dimensional feature space where similarly labelled spectrogram images are compacted near to each other in the feature space, while different labelled images are moved distant from each other. The accuracy of this BCI classifier is 64.7% to classify the user's intention for the 3 motor imagery classes. It is evident that with such accuracy performance, controlling a quadcopter to pickup an object is very difficult.

IV. BCI Motion Control and and Autonomous Control of Quadcopter

Labview program has been designed for controlling a Parrot AR Drone 2.0 quadcopter. The quadcopter is controlled via the onboard WiFi connection, and flights with 3 degrees of freedom, namely forward-backward, rotate left-right and vertical moving up-down. A fourth control command used for hovering and landing down. The Labview design control receives the BCI commands from the Python script that uses Deep Learning to decode the EEG signals. The Labview sends the selected object label to the Python script that is responsible for the object detection of the selected item. Moreover, the Labview program receives the coordinates of that object, if it is within the field of view of the bottom camera of the quadcopter. And when such coordinates is detected, the Labview script switches from the BCI control mode into the autonomous mode, where it moves the quadcopter to center the x-y position of the quadcopter over the object, and picks it up using a solenoid device. The replay of the inverse kinematics replays all movements in reverse, in other words, if there was a forward movement for 5 cm/sec speed for duration of 1 sec, the replay would be the same but in the backward direction. In this phase, the object detection algorithm is detecting a special sign drawn on the wall beside the user, which is used to correct the +/- 1 meter error in the x-y plane position that may build up during the flyback replay.

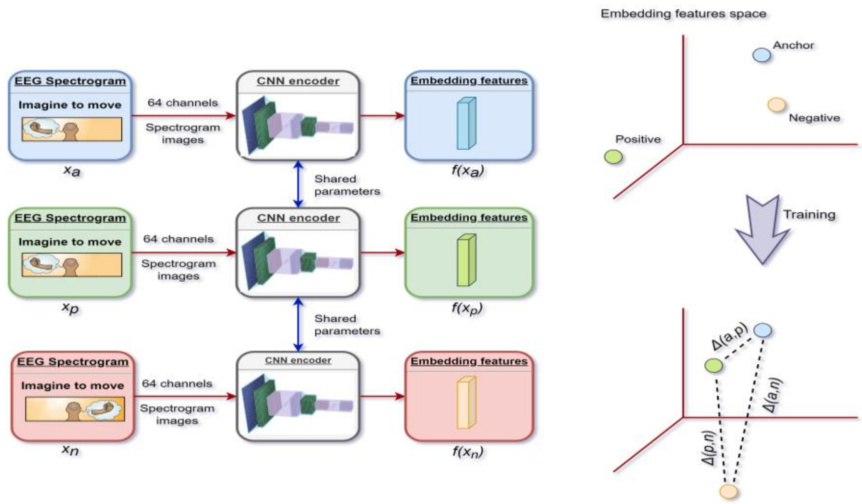

Figure 3: Triplet Network architecture. Three kind of images are used to train the network within each minibatch. The anchor imagex_a , the similar positive instance image x_p and the negative instance image x_n are are processed with 3 CNN encoders. The goal is to decrease the Euclidean distance of the embeddings difference between anchor and positive instance image $\Delta(a,p)$ and to increase the distance between the anchor and negative instance embeddings $\Delta(a,n)$

V. Object Detection

The object detection algorithm serves to aid the fine grade navigation of the drone. It uses the bottom camera of the quadcopter when trying to detect the desired object to be picked up, and the front camera when trying to navigate the drone back to the user. A deep learning approach is used using Python 3.6 and Pytorch 1.0 deep learning framework and fastai v1.0 library. In particular, the Feature Pyramid Network (FPN) design has been adopted for this task[9]. FPN is creating a pyramid of features and using them for detecting objects at different scales (Fig. 4). Generally, detecting multiple scaled images is computationally expensive, but FPN uses a feature extractor technique that facilitates such multi-scale object detection with the pyramid concept. It is generally considered a replacement for the Faster R-CNN feature extractor[10] by generating multiple feature map layers. There are two pathways in FPN: bottom-up and top-down pathways. The bottom-up pathway is an ordinary Convolutional Neural Network (CNN) that is used for feature extraction. Layer after layer, the features extracted become more abstract (with more semantic value) and the spatial resolution decreases. The top-down pathway is for constructing higher resolution layers from the higher semantic layers. Although that these reconstructed layers are semantically rich, however the locations of the objects are not precise due to the up sampling and down sampling processes. For solving this issue, the lateral connections between the layers and the corresponding maps enhances the accuracy of the location detection.

VI. Experiments

The BCI design has been validated on the Physionet Motor Imagery dataset[11], which includes motor imagery EEG trials of 109 subjects. The Triplet Network performed with an average of 64.7% accuracy on classifying the 3 labelled classes. A volunteer has been trained to use the BCI system and DL algorithm showed slightly better performance (71%) than the validation set of the Physionet dataset. However, with the combined controller and the BCI, the system is able to enhance the accuracy to around 93%, which is showing a significant enhancement over the performance of the BCI system alone.

VII. Conclusion

This paper shows architecture for an auxiliary shredded

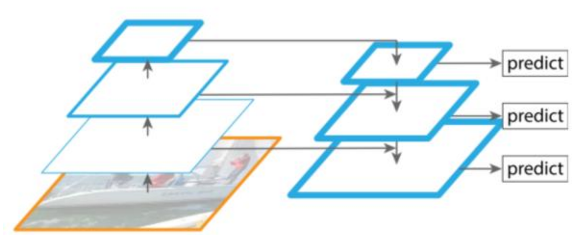

Figure 4: Feature Pyramid Network architecture[7]

control that can be used in combination with a BCI control system. The system shows a promising design for controlling devices for people with severe disabilities who intend to use a BCI system in daily-life tasks. The proposed system composed of motor imagery BCI system with Labview controller algorithm to decide when the BCI system should control the navigation of the quadcopter and when the autonomous navigation algorithm should take over.

VIII. Acknowledgments

This research is supported by the Graduate Assistantship Scheme of Universiti Teknologi PETRONAS, and by the Ministry of Education Malaysia under the Higher Institutional Centre of Excellence (HICoE) Scheme awarded to the Centre for Intelligent Signal and Imaging Research (CISIR).

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